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Measuring the Impact of Monetary Policy Attention on Global Asset Volatility Using Search Data

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Measuring the Impact of Monetary Policy Attention on Global Asset Volatility Using Search Data

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Abstract

We study monetary policy introducing a novel measure for policy attention based on Google Trends data. We apply the obtained indices to fixed income data for the US and the Eurozone in a specification motivated by a preferred-habitat model to test for monetary policy transmission domestically and internationally. Our findings suggest an impact of monetary policy on variance processes only and provides evidence for an international channel of monetary transmission on both money and capital markets. This is, to our knowledge, the first attempt to use search-engine data in the context of monetary policy.

JEL Classifications: E52, E43, E44, G10, G15

Keywords: Attention, Internet Search, Google, Monetary Policy, ECB, FED, International Financial Markets, Macro-Finance, Sovereign Bonds, International Finance, Bond Markets, Preferred Habitat Models

1 Introduction

What is monetary policy in an open economy? And how can we measure it empirically? Monetary policy has shifted towards targeting agents' expectations, giving rise to its measurement based on policy perception rather than action. Given the openness of global capital markets the presence of large central banks further affects policy transmission, which motivates an investigation of spill-overs between similar sized central banks.

The literature on global effects of monetary policy has mostly focussed on transmission between small and large central banks. Bauer and Neely

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(2014) and Neely (2015) are prominent examples. Georgiadis and Gräb (2016) offer one of the few empirical treatments considering transmission between the ECB and the Fed. But they explain this transmission through foreign exchange (FX) markets. However, Rey (2015) argues that FX markets are insufficient for independent monetary policy in the presence of unrestricted international capital flows and emphasises the presence of global financial cycles, where globally monetary policy is dominated by few large central banks whilst other central banks are limited in their policy reaction. In this case, the Mundellian Trilemma, stating that from the policy objectives of targeting exchange rates, unrestricted capital flows and independent monetary policy only two can simultaneously be met, is insufficient – there are policy spill-overs despite largely unrestricted FX and capital markets. Miranda-Agrippino and Rey (2015) provide empirical evidence for this, showing that global asset prices follow one common factor, that can be identified as the VIX volatility index. This raises the question of external effects of monetary policy beyond transmission through FX markets. Rey (2016) specifically investigate an international channel of monetary transmission by fitting a VAR model with exogenous 2SLS identification to data on a group of economies with freely-floating exchange rates, using instruments similar to those applied in Gertler and Karadi (2015) [1]. However, the Eurozone is excluded from this analysis, and the observed transmission is therefore again between a large economy and several small economies.

Linking into this is the more general question of policy measurement and transmission, which has traditionally been tackled in general equilibrium models, assuming market completeness for tracktability (Christiano et al. (2005), Smets and Wouters (2003)). Whilst such DSGE models are able to replicate macroeconomic series, they fail to produce sufficiently large term spreads on the fixed income market (Rudebusch and Swanson (2008)). The existence of such a bond premium puzzle motivates partial equilibrium analyses assuming segmentation of the fixed income market. Krishnamurthy and Vissing-Jorgensen (2007) and Krishnamurthy and Vissing-Jorgensen (2011) give empirical evidence for the segmentation of the fixed income market. Vayanos and Vila (2009) formalise this in a preferred-habitat theory of the fixed income market, which is extended in Hamilton and Wu (2012), and Altavilla et al. (2015), who include a credit premium channel.

On the analysis of policy transmission, the literature almost unanimously highlights the importance of communication as a policy tool. Analyses of policy announcements are typically carried out with event-studies, which

[1] Gertler and Karadi use high-frequency surprise factors, following Gurkaynak et al. (2004), ie. surprises in FOMC announcements, measured in event-studies as response of different fed funds futures rates within 30 minute windows to individual announcements. The surprise factors received through this exercise are then in the first stage used as instruments for either a policy rate or a 1- or 2-year government bond. In the second stage, different market interest rates are regressed on the instruments.

are commonly used in corporate finance to evaluate the impact of particular events on the price of a security. Kothari and Warner (2004) offer a review of the respective corporate finance literature. In macro-econometric applications event studies are entering through surprise factors as introduced by Kuttner (2001) with a prominent application in Gurkaynak et al. (2004), where event studies are used to identify policy shocks through observing changes in policy-rate futures over narrow intra-day (typically 30-minutes) event windows, which, accumulated over a given frequency (typically monthly), can be used as explanatory variables in ordinary regressions. Further examples include Bernanke et al. (2004), Bernanke and Kuttner (2005) and Lenza et al. (2015), who study ECB liquidity measures in an event study of announcements on its Outright Monetary Transactions (OMT) programme, finding a significant impact on a set of European government bond yields and macroeconomics variables. Bauer and Rudebusch (2013), investigates the signalling channel of monetary transmission, i.e. announcements signalling commitment towards the future path of short-term rates, with event study evidence, using term premia obtained through a dynamic term structure model. However, the use of intra-day identification strategies for policy can be problematic for several reasons: Lucca and Moench (2015) observe an anticipative effect on equity markets prior to FOMC announcements, that they call "Pre-FOMC announcement drift". Whilst they cannot infer any significant drifts for money market futures or fixed income markets, it illustrates problems regarding intra-day identification. The question of how much information is reliably extracted within 30 minutes of monetary policy announcements adds to this.Gurkaynak et al. (2004) compare the use of intra-day to daily event windows. Their results show only small changes in magnitude of the observed effects but substantial increases in the model fit.[2]

Adding to this is a selection bias: Event-datasets are typically based on a set of chosen key announcements. A branch of the literature has addressed this, considering news-data to verify the dominance of monetary policy announcements in the market. Altavilla et al. (2015) and Krishnamurthy and Vissing-Jorgensen (2011) both follow this approach. News-data is also commonly employed in measures of economic uncertainty. In a seminal paper Bloom (2009) highlights the importance of uncertainty shocks for the macroeconomy. Baker et al. (2016) build on this with the introduction of Economic Policy Uncertainty (EPU) indices, measuring investor sentiment based on newspaper coverage. Da et al. (2011) show that weekly GoogleTrends data gives a direct measure for investor attention, leading traditional measures such as excess returns. Da et al. (2015) extend this, using GoogleTrends

[2]A daily surprise factor using 3m-T-Bills, gives an R^2 of 56%, compared to 77% and 80% for intra-day data.

data to construct a FEARS [3] index to measure investor sentiment. Choi and Varian (2012) show a broad set of potential applications for Google data in forecasting and Carrière-Swallow and Labbé (2013) use Google data in a now-casting context.

In this paper, we address the aforementioned gaps in the literature, introducing a measure of monetary policy attention through indices based on a set of search words obtained through Google Trends. We show that the indices capture a set of identified events and are exogenous in the model specification used. We then apply the indices in an empirical case-study of monetary policy interaction between the ECB and the US Federal Reserve on fixed income markets between 2014 and mid 2016. With this research we add to existing literature twofold: We introduce a high frequency measure on monetary policy attention, which significantly informs policy relevant variables. We further add to the growing literature on the international transmission of monetary policy, providing evidence on volatility spill-overs between two similarly sized central banks.

The remainder of this paper is structured as follows: The next section discusses our estimation strategy, section 3 gives an overview of our data and derives the construction of the search indices and section 4 gives results. Section 5 offers a conclusion and an outlook.

2 Estimation Strategy

We employ a modified version of the model proposed by Altavilla et al. (2015), to model yields as a function of the average expected future risk-less benchmark rate, a credit and a volatility premium [4]:

$$\mathbf{y}_t = \frac{1}{T}\sum_{i=1}^{T} \mathbb{E}\mathbf{r}_{t+i} + CP(\boldsymbol{x}, \iota) * VP(\gamma, \lambda(\sigma, \omega(S, \xi), \bar{b}, \gamma), \mathit{\Sigma}\mathit{\Sigma}'). \qquad (1)$$

(1) can empirically be decomposed in a mean process and a conditionally heteroskedastic variance process. We use money market futures[5] as proxies for the average expected future risk-less benchmark rate. The credit and volatility premiums, CP and VP, then constitute the variance process, which might itself affect mean yields, given by the 8×1 vector of yields, $\boldsymbol{y}_t$. The credit premium captures the default probability of an asset at maturity and would hence be affected by the vector of structural macroeconomic variables, $\boldsymbol{x}$, as well as a term, ι, collecting the parameters γ and μ. It will

[3] Financial and Economic Attitudes Revealed by Search

[4] See Appendix C for an outline of the model.

[5] We use one-month fed funds futures as proxies for US risk-less benchmark expectations and the one-month EONIA futures as the equivalent for European markets.

be captured as autonomous factors by the intercept of the variance equations. The volatility premium, VP, depends on the market price of risk, λ, the credit-risk intensity coefficient of macro-factors, γ and a stochastic disturbance term, $\Sigma\Sigma'$.

We will pay most attention to λ. It captures the product of arbitrage demand, ω, risk-aversion, σ, and the pricing- and credit-risk coefficients of macro-factors, b and γ. We assume the latter coefficients to be again constant and hence captured in the intercepts of the variance processes. σ is estimated as implied market risk, measured by the VIX implied volatility index. ω is the difference between asset supply, S, and (preferred-habitat) asset demand, ξ, which follows directly from the market clearing condition. Monetary policy affects bond supply, available to the private sector. Hence our policy indices enter ω (and hence λ) via S.

Translating these theoretical results into an empirical strategy, we proceed in steps:

Step 1: Mean Specifications. We begin by estimating (1), considering the mean process of yields only and proxying expected returns as outlined above, hence

$$\begin{aligned} y_t^i = c + \beta_1 y_{t-1} + \beta_2 \upsilon_{t-1} + \beta_3 ff_{US,t} + \beta_4 ff_{EU,t} + \beta_5 ECB \\ + \beta_6 FED + \beta_7 VIX + \sum_{j=1}^{k} a_j y_{t-1}^j + \upsilon_t, \\ \forall i \neq j. \end{aligned} \tag{2}$$

$ff_{US,t}$ and $ff_{EU,t}$ are US and Eurozone policy rate futures, ECB and FED are the European and US Google based monetary policy search indices, and the summation term includes (unidentified) VAR terms. υ_t is a heteroskedastic variance process that we will focus on in the second stage below. We compare different specifications, based on the Schwartz-Bayes Information Criterion, by building up the model in stages from a random walk with drift to the full specification, given in (2). Following the estimation exercise in (2) we estimate y_t^i as a function of the first term in (1), the policy indices and include ARMA and VAR terms. In addition to the theoretically derived specification and common time series specifications, this allows to test, if any of the remaining variables, i.e. the policy indices and VIX, affects mean yields directly.

Step 2: Variance specifications. In this stage we focus on the premia, CP and VP in (1) and hence on specifying the variance processes. We assume a time-varying variance process that does not exhibit cross-correlation between yields (i.e. a diagonal conditional correlation matrix), which we specify as EGARCH(1,1,1) models. We assume the mean specification selected following step 1 above, hence

$$y_t^i = b_0 + b_1 DVIX + \upsilon_t \tag{3}$$

where

$$\upsilon_t = \varepsilon h_t^{1/2}, \quad \varepsilon \sim IID(0, \Sigma\Sigma')$$

and

$$\begin{aligned} \log h_t &= c_0 + c_1 h_{t-1} + c_2 |\frac{e_{t-1}^2}{h_{t-1}}| + c_3 \frac{e_{t-1}^2}{h_{t-1}} \\ &\quad + c_4 VIX + c_5 ECB_t + c_6 FED_t. \end{aligned}$$

h_t follows a EGARCH(1,1,1)-process, c_0 is a constant, the first three terms in the variance equation represent ARCH and GARCH terms and an asymmetry parameter, with their respective coefficients, c_1 - c_3. The terms in the mean equation are specified as before, where inclusion of any of the variables is based again on BIC. The specification in (3) above is our *baseline specification*. In addition, we consider the effect of differences in exchange trading hours and GARCH-in-Mean effects.

Step 3: Variance Correlations. The third step analyses the correlation matrix of an unrestricted VAR of all variables,

$$y_t = A_1 y_{t-1} + A2 y_{t-2} + \epsilon \tag{4}$$

$$\Delta y_t = \Delta A_1 y_{t-1} + \Delta A2 y_{t-2} + \vartheta, \tag{5}$$

where y is a column vector of all N variables A_1 and A_2 are $N \times N$ coefficient matrices, ϵ and ϑ are $N \times N$ variance-covariance matrices. We assume the covariance matrices non-diagonal and constant over time. Estimating this stage allows us to detect potential cross-correlation between assets, which is not considered given the diagonality assumption on the variance-covariance matrix in the preceding step.

3 Data

We use two main data sources for our research – a set of fixed income indices to measure market reaction and data on online search engine queries, gathered through Google trends. We employ daily data sample spanning from January 2014 to June 2016. This dataset marks a time where monetary policy between US Fed and ECB diverged, which accommodates the analysis of spill-over effects. We only consider US and Eurozone data, due to the similar size of the currency areas. The choice of daily data allows us to observe volatility clusters, which we exploit in our web search indices as measures for monetary policy attention. Variables are differenced, where appropriate, based on ADF tests. A list a variables is reported in tables 1 and 2 below. We distinguish policy indices, VIX and futures, which enter our models exogenously, and the remaining variables entering endogenously.

Table 1: Variables and Datasources – Endogenous Variables

Label	Variable	Unit	Source
XOIS	European Overnight Index Swap Rate	%	Reuters Datastream
XCORP_HY	IBOXX EUR Liquid Corp. HY Index	% Yield	Reuters Datastream
XCORP_Y	IBOXX EUR Liquid Corp. Index	% Yield	Reuters Datastream
XBUND	10-year German Government Bonds	% Yield	Reuters Datastream
USOIS	US Overnight Index Swap Rate	%	FRED
US_CORP_HY	BoAML US Corp. Master Effective Yield Index	% Yield	FRED
US_CORP	BoAML High Yield Effective Yield Index	% Yield	FRED
US10Y	10-year US Government Bonds	% Yield	FRED

Notes: Variables are differences; prefix 'X' indicares USD-converted variables.

Table 2: Variables and Datasources – Exogenous Variables

Label	Variable	Unit	Source
XEONIA	1Month EONIA Futures Rate	%	Quandl
USFF1M	1Month Fed Funds Futures	% Yield	FRED
VIX	Chicago Bond Options Exchange Volatility Index	Index Value	FRED
ECB	ECB Monetary Policy Search Index	Index Value	Google/ own calculations
FED	FED Monetary Policy Search Index	Index Value	Google/ own calculations

Notes: All variables (apart from ECB and FED) are differenced; prefix 'X' indicares USD-converted variables.

3.1 Financial Data

European government bond yields are based on data for German 10yr "Bunds", which is a canonical choice as a risk-less asset on European capital markets. For US government bond markets we employ 10yr Treasury Notes. Overnight index swap (OIS) rates capture the short end of the money market, both in Europe and the US. Lower credit fixed income instruments are captured using two European corporate bond indices, IBOXX EUR Liquid Corporates BBB and IBOXX EUR Liquid Corporates from Markit, and two US indices[6], Bank of America Meryll Lynch's US Corporate Master Effective Yield Index and its High Yield Effective Yield index. The choice for those particular indices is owing to their high market liquidity. We further

[6]Both, the European as well as the US bond indices, are each mutually exclusive in the sense that they define clear rating thresholds, currency inclusion criteria and are provided through the same respective sources. This ensures that at every point in time each security can only be captured once, and hence avoids double-counting.

use the Chicago Board Options Exchange Volatility Index, VIX, which measures implied market volatility, as a proxy for global market risk, and 1mth Fed Funds and EONIA Futures rates as proxies for market rate expectations. All European futures and fixed income series are converted to USD. An overview of data sources is given in table 1.

Figure 1: Financial Series

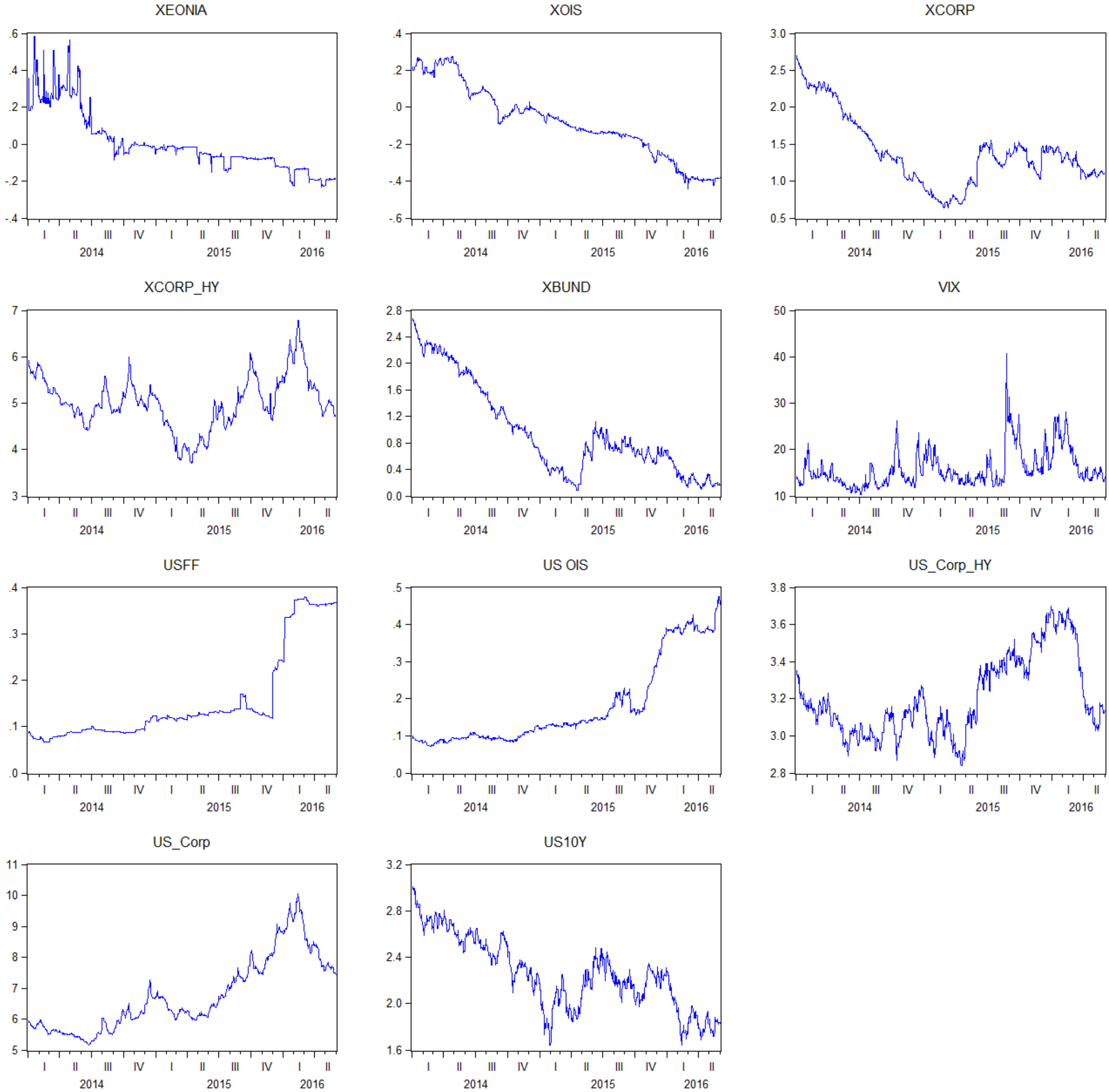


Figure 1 plots the raw series for financial data used for this analysis. The vertical axis measures interest in percentage for all series but the VIX, where prices are plotted instead. From a quick inspection of the graphs, a few patterns become immediately apparent: The fixed income series, appear to have unit roots and exhibit co-integration and there appears to be a period of heightened volatility on European markets towards the end of 2015 and on US markets in the first half of 2016. This coincides with key monetary policy announcements, regarding the introduction of a quantitative easing programme in Europe and of a rate contraction in the US. The observation of diverging policies between Fed and ECB is further supported by the widening spread of both money market futures and OIS rates between the two currency areas. Descriptive evidence, hence does suggest a divergence of monetary policy cycles and announcements to have had an impact on fixed income markets.

3.2 Google Data

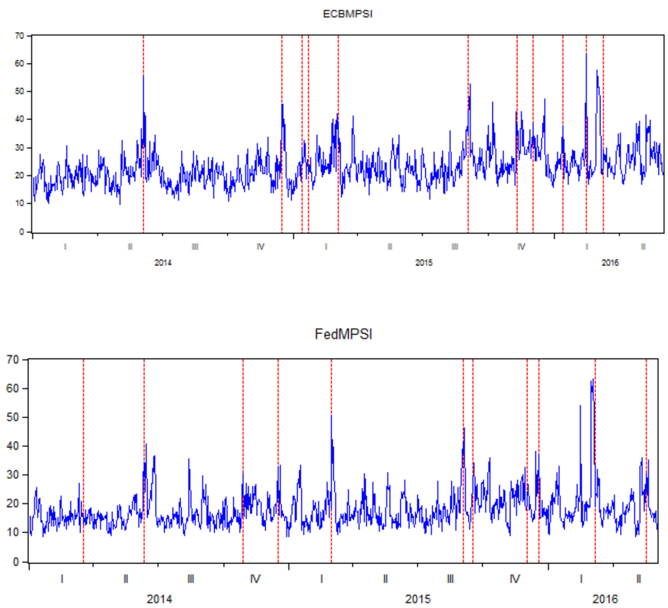
Announcements, News and Uncertainty We use news data to measure monetary policy attention as a proxy for policy. This approach follows a well established branch of event study literature pioneered by Fama et al. (1969), Gurkaynak et al. (2004) and Bernanke et al. (2004), where policy is measured as policy announcements rather than policy implementation. A common approach in the literature is to define a set of dates at which relevant announcements are suspected, such as central bank policy meetings. This rests on the assumption that announcements will always be released in a controlled way and on a choice of announcements that is deemed relevant.

Using news data deviates from this idea in a more agnostic approach in that it does not assume knowledge of announcements and hence avoids the identification of particular events. Instead, whenever certain patterns of news coverage are observed it is assumed that policy relevant events took place. In that sense, our indices are measures of policy attention that reflect a revision of agents' expectation formation, which affects policy relevant target variables and thereby gives a proxy for policy itself. Lenza et al. (2015) follow this approach implementing a news-intensity index based on the frequency of news articles containing a set of pre-defined words. Baker et al. (2016) introduce an index of uncertainty obtained from news data. Da et al. (2011) propose attention measures based on Google data and Da et al. (2015) extend these results to construct an index for investor sentiment.

MPSI Index Construction The Monetary Policy Search Index (MPSI) uses an index based on a number of search queries related to one particular central bank investigated. Following Da et al. (2015), the index is built as a weighted average of GoogleTrends Search Volume Indices (SVI) on search words correlated with the search topics "European Central Bank" and "Federal Reserve System". The selection of individual search terms is based on a number of Google's suggested *related searches*, which are search terms entered by the same users. The associated correlation measures enter as index weights. This approach avoids spurious relationships, which might be present using other uninformed correlation measures.

The search indices for ECB and Fed related searches are plotted in figure 2. The vertical lines represent identified events, which are given in appendix A3. We can observe that the indices exhibit strong volatility, owing partly to noise, but we can also see that they are clearly heteroskedastic and can even identify several volatility spikes and clusters that coincide with policy events. The most significant events seem to be relating to the launch and extension of asset purchases for the ECB and interest rate hikes for the Fed, which is in line with patterns we observed for the fixed income series. Identifying particular events using our indices is not a comprehensive exercise, which would compromise the very reason for using such measures, but provides evidence that the MPSI measures capture relevant policy events and do not just follow noise.

Figure 2: Google Search Indices and Identified Events



Notes: Vertical lines represent individual identified events. Vertical axis gives a search volume index value based on normalised index values obtained through Google Trends for individual search words (see appendix A.3 for details). Data source: Google Trends (www.google.com/trends)

Working with Google Trends Data Google Trends provides data on web searches through the Google search engine. Through its web-interface [7], users can download a search volume index that gives the number of searches for a particular search term within a time-frame as a share of the total number of searches over that time. The length of the time frame depends on the frequency of the data used - i.e. one day for daily data etc. The index is then normalised against the highest observation within the reported time sample, which is by default scaled to 100. Theoretically, data is available in monthly, weekly, daily and intra-daily frequency. However, Google limits the size of its reports to 90 observations. To obtain daily data (for more than 90 days) requires re-indexation of the data since the default normalisation would otherwise force cyclical behaviour on the data. [8]

Using Google data can also cause a sampling error as SVIs are based on a random sample of actual search data. These resulting sampling errors are well documented in the literature[9] and concluded to be small. They are most relevant in the context of real-time analyses, where data is downloaded and updated over long periods of time (Carrière-Swallow and Labbé (2013) and Choi and Varian (2012)). Li (2016) evaluates the sampling error in the context of nowcasting modelling and observes an effect on significances across different search terms used. This is unsurprising since the size of the sampling error is likely related to the size of the underlying true populations for that search term. They conclude as best practise to download several series from different IP addresses within one day and use an average of the downloaded samples. As real-time data is not applied in our research and described biases are reported to be small, we judge this issue to be negligible.

Search words used for the construction of the MPSI search indices are reported in table 7 in Appendix A3.

4 Results

To discuss our results, we first address model selection and different specifications of the mean processes and draw first comparisons with theoretical predictions. We then turn to variance processes, where we consider two robustness exercises in addition to a baseline specification as laid out in eq. (3) above. Lastly, we consider evidence from residual correlations of unrestricted VARs in levels and first differences to address volatility-correlations of the assets considered.

[7] trends.google.com

[8] We follow http://www.clintonboys.com/google-trends-scraper/ and http://erikjohansson.blogspot.co.uk/ for re-indexation.

[9] see Li (2016)

4.1 Testing Mean Specifications

We follow the specification tests outlined in step 1 on of section two. Table 5 below gives the BIC values for the models considered. The last column reports the sum of all the individual BIC values accross models for one particular specification. We find that mean yields are best specified by regressions on VIX and a constant. In particular, this suggests that policy and money market rates do not directly affect mean yields. The presence of VIX in the mean processes might capture the volatility premium and provides evidence in support of global financial cycles.

Table 3: BIC for Alternative Mean Specifications

Mean Specification	XOIS	US10Y	US_CORP	US_CORP_HY	US_OIS	XBUND	XCORP	XCORP_HY	SUM BIC
RW	-7.42*	-3.79	-3.41	-4.46	-8.77	-3.97	-4.61	-3.43	-39.86
RW+VIX	-7.41	-4*	-3.49*	-4.56*	-8.78*	-4*	-4.61*	-3.46	-40.31*
ARIMA(1,1,0)	-7.42	-3.78	-3.43	-4.45	-8.77	-3.96	-4.607	-3.48*	-39.897
ARIMA(0,1,1)	-7.42	-3.78	-3.43	-4.44	-8.77	-3.96	-4.607	-3.47	-39.877
ARIMAX(1,1,0)	-7.4	-3.77	-3.41	-4.44	-8.77	-3.94	-4.59	-3.43	-39.75
MPSI+ARIMAX(1,1,0)	-7.4	-3.75	-3.39	-4.42	-8.76	-3.93	-4.58	-3.42	-39.65
VIX+ARIMAX(1,1,0)	-7.4	-3.99	-3.5	-4.55	-8.78	-3.98	-4.6	-3.45	-40.25
VAR+ARIMAX(1,1,0)	-7.36	-3.72	-3.37	-4.39	-8.73	-3.9	-4.54	-3.47	-39.48
VAR+MPSI+ARIMAX(1,1,0)	-7.34	-3.7	-3.35	-4.37	-8.71	-3.89	-4.52	-3.45	-39.33

Notes: Table gives Bayes-Schwarz Information Critera (BIC) for different mean specifications given in the first column. RW: Random Walk with drift, AR and MA: auto-regressive and moving-average terms, ARIMAX(1,1,0) includes futures as exogenous variables; MPSI includes ECB and FED as exogenous variables; VAR considers lags of all assets apart from each dependent variable.

4.2 Univariate GARCH Estimates

We report estimates based on a set of t-distributed EGARCH models. Using t-distributed GARCH models is motivated by the high frequency of the data, giving leptokurtic error-processes. [10] The models are specified as in equation (3). The mean specifications follow the results of the preceding section, considering only VIX and a constant term. The variance specifications consider VIX and the policy indices as explanatory variables. The results of the models are reported in tables 4 below and in tables 9 and 10 in Appendix C.

[10] Some of the obtained estimates, particularly variances and degrees-of-freedom, were at the edge of the parameter space, which suggests fatter tails than could be replicated in a t-distribution. We therefore re-estimated the models assuming a generalised error distribution, yielding similar results. We disregarded these estimates for further analysis. Possible explanations for this might be the presence of outliers. But since we could not observe common outliers across all variables, we abstained from excluding any observations.

Baseline GARCH Specification Considering the US fixed income market, we find evidence for spill-over effects on both money and capital markets. ECB is significant in US_OIS and US_CORP the policy instruments are both significant for US_OIS and $XOIS$. US policy, does only appear to affect capital markets as FED remains insignificant for US_OIS but enters significantly in all other US models. This could be as a result of unconventional policies specifically targeting the longer end of the yield and the lower end of the credit curve.

For Europe we find evidence for policy spill-overs on money markets only – FED only enters $XOIS$ significantly. As before, there is evidence of domestic policy effects, as ECB enters significantly in $XBUND$ and $XCORP$, albeit less so than for the American series. It is interesting to note significant policy effects across almost all assets considered, particularily the investment grade coporate markets. This indicates that policy appears to have been effective in by-passing the traditional bank-lending channel. Furthermore, note that, apart from $XCORP$[11], none of the coporate bond segments have been directly targeted by central bank asset purchases. Reactions in those indices hence provides evidence for transmission via portfolio-rebalancing. However, this interpretation comes with a note of caution as we observe contributions to variance processes and can only make limited judgements on the direction of these variations based on the descriptive evidence provided in figures 2 and 3 in section 4.1 above. Noting the trends apparent in the data we can assume that the impact should be positive on US and negative on European yields, which is in line with ECB policy expanding further whilst the FED withdrew policy accommodation over the sample period. It is again interesting to find VIX entering significantly in both, variance and mean processes. For the former, we only find a modest contribution mainly on US money markets. On the latter it is highly significant on almost all market segments considered. Excluding corporate bonds VIX affects yields negatively, which, considering the inverse relationship between yields and prices, indicates a positive relationship between prices for safe assets and risk. Similarly, it is unsurprising to find that relationship reversed for riskier corporate bonds. In that sense it is more surprising to not find that sign reversal for $DXCORP$ and DUS_CORP_HY, which might be a result of local supply characteristics. [12] Lastly, we find significant GARCH

[11] As of 01/06/2016 the ECB engaged in investment grade corporate bond purchases within its Corporate Securities Purchase Programme (CSPP). To a large extend the CSPP has been anticipated. This might be picked up by $XCORP$, which would then indicate effects of direct policy interventions rather than portfolio-rebalancing.

[12] With the CSPP ECB extended asset purchases towards investment graded which excluded high yield corporate bonds. There are also regulatory differences between investment and sub-investment graded corporate bond segments in that the latter is commonly treated as speculative assets. As a result, there might be less friction between money, government and investment grade corporate bond markets on one hand and sub investment graded markets on the other.

effects in half of the models whilst there is no evidence of ARCH or leverage effects.

In summary, the results of this exercise suggest international effects of policy, as measured by our indices, on both, money and capital markets, for the US and on money markets for the Euroarea. It further suggests domestic effects throughout different credit segments in both the US and Europe. For the US, there is also evidence of portfolio-rebalancing.

Table 4: EGARCH Models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	*US_OIS*	*US10Y*	*US_CORP*	*US_CORP_HY*	*XOIS*	*XBUND*	*XCORP*	*XCORP_HY*
Mean Equation								
C	8.27E-05	-0.000821	-0.000573	-0.000665	-0.000182	**-0.001477***	**-0.001230****	**-0.002101****
	(1.201929)	(-0.979054)	(-0.567386)	(-1.506669)	(-1.359356)	**(-1.758433)**	**(-2.063785)**	**(-1.956880)**
VIX	**-0.000363*****	**-0.015963*****	**0.012238*****	**-0.006992*****	**-0.000157***	**-0.005107*****	**-0.001627*****	**0.007015*****
	(-6.816837)	**-26.69563**	**(15.10092)**	**(-15.61869)**	**(-1.753395)**	**(-8.325512)**	**(-3.621788)**	**(8.236160)**
Variance Equation								
C	-6.960750	-3.662015	3.073327	-4.441654	-2.569310	2.865323	-2.214482	3.577638
	(-0.872901)	(-0.388372)	(0.020390)	(-0.549369)	(-0.042524)	(0.010400)	(-0.041745)	(0.010826)
ARCH	20.44661	5.348404	155.5151	5.951210	51.63544	117.2196	11.11799	134.1159
	(0.290274)	(0.277227)	(0.013698)	(0.349205)	(0.034565)	(0.006978)	(0.039883)	(0.005876)
Leverage	3.885094	0.403395	18.69268	-1.576078	-5.017070	35.75017	0.120822	31.91964
	(0.286310)	(0.257894)	(0.013702)	(-0.345037)	(-0.034562)	(0.006977)	(0.036414)	(0.005876)
GARCH	**-0.140841****	**-0.311574*****	-0.032728	**-0.416927*****	-0.043762	0.039020	-0.057923	0.029076
	(-1.985410)	**(-3.047732)**	(-0.451202)	**(-4.360583)**	(-0.786600)	(0.314563)	(-0.568688)	(0.338143)
VIX	**0.112182*****	0.052028	**0.081371***	-0.049157	0.026983	**0.096461****	-0.005116	0.035915
	(3.099007)	(1.358781)	**(1.957764)**	(-1.338626)	(-0.602928)	**(2.248105)**	(-0.128902)	(0.920422)
ECB	**0.043695*****	-0.006596	**0.031453****	-0.003569	-0.006118	**0.025148***	**0.030100*****	0.012360
	(3.170908)	(-0.462849)	**(2.246342)**	(-0.275538)	(-0.602646)	**(1.804188)**	**(2.670313)**	(0.888251)
FED	0.018162	**0.036729****	**0.042090*****	**0.027850****	**0.046660*****	0.007628	-0.010964	0.018484
	(1.254542)	**(2.428278)**	**(2.714482)**	**1.980296)**	**(4.388056)**	(0.534976)	(-0.860060)	(0.888251)
T-DIST. DOF	2.000418	2.004981	2.000008	2.004470	2.000060	2.000010	2.001112	2.000009
BIC	-8.782046	-4.003451	-3.494414	-4.561140	-7.412446	-3.997059	-4.612905	-3.455146

Significant coefficients (< 10% level) are given in bold-faced letters; significance levels: * < 10%,** < 5%,*** < 1%; z-values in parantheses; mean equations are specified based on the Schwarz criterion (see section 5.1); Estimation of all models as ML with EGARCH(1,1,1) specification assuming t-distributed errors and optimisation using the Eviews legacy algorithm with Marquard steps in all models. BIC gives the Schwarz-Bayes Information Criterion. ECB was lagged once in model (5) and FED lagged once in model (7) to avoid endogeneity problems.

Exchange Trading Hours We consider the effect of sequential market adjustment to news-shocks. Engle et al. (1988) describe this effect as *meteor showers*, which rain down as the earth rotates. Analogously, one particular news shock could be priced into markets at different times as global trading hours vary. For obvious reasons, this effect is most relevant for intra-day data. We do, however, consider it as a robustness exercise as the difference in common trading hours between US and European exchanges is sufficiently large for some US news-shocks to be priced into European markets on the next trading day. Examples for this are FOMC press conferences that are typically held after European trading hours. Table 9 hence lags variables from US exchanges by one day. The exercise confirms previous results.

GARCH-in-Mean Specification Theory suggests that market volatility directly affects mean holding returns as the volatility premia in (1) affect yields directly through spreads. To account for this, we specify a set of GARCH-in-Mean models, where GARCH terms enter mean equations with log variances. Results of the GARCH-M estimations are reported in

Table 10. Accordingly, we cannot find any evidence for GARCH-M effects. GARCH is insignificant in the mean processes of all models considered. Additionally, we cannot see improvements in model fit based on the Schwarz-Bayes measure, and have to conclude that the models are over-fitted. This suggests that the volatility premium on mean yields is captured by VIX only.

4.3 VAR Residual Correltations

We estimate unrestriced VARs in both levels and first differences as outlined in (4) and (5) above and then analyse the resulting residual correlations. We obtained similar correlations in both cases. The correlation matrices are reported in table 11 below. This exercise can be seen as following Sims (1980). We can follow this approach as we are solely interested in the analysis of correlations with respect to the variance processes of the assets considered and do not draw causal conclusions from this exercise. Accordingly, we see a strong correlation between the US High-Yield Corporate Bond Index with US Treasuries. In itself this might reflect low-rated corporate bonds following shifts of the yield curve and a certain degree of co-movements one would expect on the fixed income market. It is somewhat surprising though to find such a strong correlation for lower rated corporate bonds, whilst the investment-graded index only exhibits a small and even negative correlation with Treasuries. The negative correlation indicates some degree of portfolio shifts as yield-compression for high quality assets pushed demand further along credit ratings, but yet not enough to cause the same effect for the High-Yield segment. Hence, this provides evidence for both the segmentation of the fixed income market and some degree of portfolio shifts. We can also see some co-movement of US and European rates: German 10-year government bonds are positively correlated with Treasuries and US corporate bonds (investment grade), albeit to a lesser extend, and we do find some correlation of the IBOXX EUR corporate bond index with US Treasuries and the US High-Yield market, but strikingly not with US investment-grade bonds. The latter might again be due to market segmentation: Investors on the American investment-graded corporate bond market might face a similar burden to invest in European bonds than to invest in the High-Yield market.

Lastly, there is some (weak) correlation of VIX with the observed rates, with the strongest correlations, unsurprisingly, for American rates, particularly US_CORP and $US10Y$. The strongest correlation, the American corporate bond index, is positive, which is what we would normally expect – an increase in risk, measured as implied volatility in VIX, leads to a drop in demand for corporate bond issues, and hence an increase in yield. Somewhat surprising is thus to find the negative correlation for the High-Yield index, where this risk-off effect should be more pronounced. The correlation for Bunds and Treasuries reflect the save-haven properties of the assets.

5 Conclusion and Outlook

We introduced a measure for monetary policy attention based on Google Trends data, which we applied in a high-frequency analysis of international monetary policy spill-overs on the fixed income market between ECB and FED. The analysis of policy transmission was informed through a preferred-habitat model, introduced in section 2 and Appendix D, that predicts policy shocks to enter yields through their variance processes. To accommodate this empirically, we proceeded in three steps: specification of the mean processes, specification of the variance processes assuming no variance correlations between assets, and an analysis of residual correlations based on an unrestricted VAR. We accounted for domestic market segmentation by considering corporate bond indices alongside government bonds, and for international market segmentation by regressing on European as well as US assets using both domestic and foreign policy indices.

Our descriptive evidence in figure 2 shows that our indices capture key policy events, reported in table 5 in Appendix A2, and the tests reported in table 8 (Appendix B) confirms that they enter our models exogenously. Our results suggest that policy shocks do not affect the information contained in mean equations of yields and on average the best mean specification follow random walks with drift and the VIX as only explanatory variable. This implies that the price discovery effects on mean asset returns through news, observed in Andersen et al. (2007) for ultra high-frequency data disappear on daily frequencies, which supports Lucca and Moench (2015). Mean specifications are summarised in table 3 of section 4.1. Based on the results of the second stage, given in tables 4, 9 and 10, policy shocks have a significant impact on the on the volatility of domestic corporate bonds, providing evidence for portfolio-rebalancing. This is in line with the preferred-habitat literature, as well as Aksoy and Basso (2014), who emphasise the effect of banks' portfolio-choice on term-spreads in a general-equilibrium setting. There is further evidence for international transmission of volatility on money and corporate bond markets, whilst there is no conclusive evidence on government bond markets. Furthermore, VIX enters significantly in all mean processes, and significantly in variances for US and European government and US investment grade corporate bonds, which supports Rey (2015). Given the absence of GARCH-in-Mean effects (table 8), the effect of the volatility premium on mean yields appears to be captured by the VIX only. However, VAR residual correlations, reported in table 11, reveal considerable asset cross-correlations, particularly in the two corporate bond habitats. This suggests the need to consider cross-correlations in the variance equations, which is beyond the scope of this paper, where the focus was on the introduction of new policy measures. We believe, despite this potential misspecification, the importance of such measures as well as considering time varying volatility in policy analysis could be demonstrated.

Given the above, a natural extension to our research considers cross-correlations in the variance equations using multivariate GARCH models such as the DCC approach described in Engle and Sheppard (2001) and Engle (2002). Exploiting higher frequencies of the data using realised volatility models such as in Corsi (2009) seems further promising. Lastly, a Markov regime-switching approach could account for different policy and volatility states.

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A Data Appendix

A.1 Summary Statistics

	DUS10Y	DUS_CORP	DUS_CORP_HY	DUS_OIS	DUSFF1M	DVIX
Mean	−0.001317	0.001667	−0.000238	0.000415	0.000317	0.000544
Median	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Maximum	0.144600	0.340000	0.110000	0.023000	0.097000	12.71000
Minimum	−0.146400	−0.280000	−0.090000	−0.051000	−0.025000	−5.700000
Std. Dev.	0.038515	0.058835	0.027533	0.004670	0.005095	1.235675
Skewness	0.170109	0.730856	0.328776	−2.180396	15.27709	1.673296
Kurtosis	4.724156	10.22032	4.731140	32.49078	281.3609	20.72367
Jarque-Bera	113.5010	1994.411	126.0238	32660.56	2881874.	11955.81
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	−1.161700	1.470000	−0.210000	0.366000	0.280000	0.480000
Sum Sq. Dev.	1.306908	3.049650	0.667850	0.019216	0.022870	1345.193
Observations	882	882	882	882	882	882

	DXOIS	DXEONIA	DXCORPBBB_Y	DXCORP_Y	DXBUND	ECBMPSI	FEDMPSI
Mean	−0.000683	−0.000621	−0.001885	−0.001799	−0.002863	23.13523	18.11248
Median	0.000000	0.000000	0.000000	0.000000	0.000000	21.95098	16.66327
Maximum	0.063661	0.280992	0.356700	0.206408	0.232899	63.15686	63.18367
Minimum	−0.079973	−0.302598	−0.401177	−0.157642	−0.157318	9.784314	8.489796
Std. Dev.	0.009377	0.031326	0.041929	0.029886	0.038703	6.806422	6.573908
Skewness	0.059543	−1.290578	0.457923	0.995138	0.849079	1.463685	2.373662
Kurtosis	20.06642	42.78481	24.08114	11.96208	8.640097	7.055266	12.93992
Jarque-Bera	10704.43	58413.89	16363.05	3097.296	1275.021	919.2894	4459.215
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	−0.602639	−0.548059	−1.662709	−1.586749	−2.524788	20405.27	15975.20
Sum Sq. Dev.	0.077469	0.864569	1.548816	0.786883	1.319688	40814.42	38073.53
Observations	882	882	882	882	882	882	882

A.2 Identified Events

Table 5: Identified ECB Events

Date	Event
05/06/2014	GC Meeting: Deposit rate from 0% to -0.1%; Refi rate from 0.25% to 0.15%; 4yr TLTRO, QE hint
16/12/2014	Bundesbank's Weidmann raises concern over QE
14/01/2015	ECJ Advocate General Approves of OMT
05/03/2015	GC meeting: Announcement to start purchases, as markets raise doubts on ECB's ability to conduct purchases; ELA extension (Greece)
09/03/2015	Benoit Coere confirms 3.2bn in purchases (as targeted)
03/09/2015	GC meeting: Hint towards further asset purchases
11/11/2015	Rumors ECB might engage in municipal bond purchases
03/14/2015	12/2015 GCM minutes released
21/01/2016	GC meeting: Draghi hints further asset purchases
15/02/2016	Dovish Draghi Speech at EP
10/03/2016	GC meeting: Deposit rate cut to -0.4; QE extension to 80bn/m, incl. corporate bonds

Table 6: Identified Fed Events

Date	Event
14/06/2014	Stanley Fisher appointed FOMC vice chair
29/10/2014	QE ended
17/12/2015	FOMC "paitent to raise rates"
02/03/2015	Appointment of Patrick Harker to succeed Charles Plosser at Phil. Fed
04/09/2015	Disappointing jobs report
17/09/2015	Dovish FOMC meeting
02/12/2015	Yellen hints rate hike
18/12/2015	First rate hike
07/03/2016	Comments from Fed's Brainard and Fisher
18/05/2016	FOMC minutes

A.3 Search Words Used in Index Construction

Table 7: MPSI Indices – Search Words

Index	Search Words	weight
MPSI	European Central Bank	100
	ECB	55
	ECB rate	40
	EZB	25
	BCE	15
	Banco Central Europeo	5
	Banca Centrale Europea	5
	Europaeische Zentralbank	5
	Banque Centrale Europeenne	5
MPSI*		
	Federal Reserve	100
	Fed	65
	Federal Reserve System	60
	Fed interest	5
	Fed rate	5
	Federal Reserve Bank	5
	The Fed	5

The search words are selected by querying the search topics "European Central Bank" and "Federal Reserve System" with the Google Trends UI, where the search is limited to News Search only. Google reports a number of statistics with each search term queried. We use "related queries" from which we select the most popular search queries. The given metric for those related queries is then used as a weight in our indices. These metrics are described in the Google Trends UI as "Scoring is on a relative scale where a value of 100 is the most commonly searched query, 50 is a query searched half as often, and a value of 0 is a query searched for less than 1% as often as the most popular query."
We follow the same approach in the construction of our control indices.

B Exogeneity of MPSI Series

We consider weak exogeneity of ECB and FED through orthogonality between residuals, obtained from a first-stage regression on the policy indices, and mean yields of the assets considered, hence

$$MPSI\_RESID_i \perp y_i$$

in

$$y_i = c + VIX_t + MPSI\_RESID_i$$

where

$$MPSI_t = MPSI_{t-1} + MPSI_{t-2} + MPSI_{t-3} + \sum_{j=1}^{7} y_j + MPSI\_RESID_i$$

$\forall i \neq j$.

MPSI considers either of both indices, i.e. ECBMPSI or FEDMPSI. The condition is violated for significan $MPSI\_RESID_i$. Table 8 below gives the resulting t-statistics. We find endogeneity in model (5) for the ECB index only and a borderline case for the FED indices in (7) and (8). In these cases we lag the indices (the dependent variables in the first stage) once to satisfy exogeneity with t-statistics of -0.36, 0.5 and 0.8, respectively.

Table 8: Endogeneity Tests

Dep Variables	(1)	(2)	(3)	(4)
Residuals	DUS_OIS	DUS_10Y	DUS_CORP	DUS_CORP_HY
$ECBMPSI\_RES_i$	0.778665	1.397571	-0.143735	-0.313435
$FEDMPSI\_RES_i$	0.736807	0.571022	0.043745	-0.303685
	(5)	(6)	(7)	(8)
	DXOIS	DXBUND	DXCORP_Y	DXCORP_HY
$ECBMPSI\_RES_i$	2.246291	0.915615	1.568577	0.115936
$FEDMPSI\_RES_i$	-1.196761	0.071963	1.755469	1.830374

C Tables for Section 3

Table 9: EGARCH Models – Accounting for Non-Dexterity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	$DUS\_OIS(-1)$	$DUS10Y(-1)$	$DUS\_CORP(-1)$	$DUS\_CORP\_HY(-1)$	$DXOIS$	$DXBUND$	$DXCORP\_Y$	$DXCORP\_HY$
Mean Equation								
C	9.95E-05	-0.000874	-0.000605	-0.000669	-0.000179	**-0.001416***	**-0.001236****	**-0.002477****
	(1.455980)	(-1.040752)	(-0.595493)	(-1.063829)	(-1.331533)	**(-1.647228)**	**(-2.044889)**	**(-2.383513)**
DVIX(-1)	**-0.000332*****	**-0.015920*****	**0.012285*****	**-0.007003*****	**-0.000168***	-0.000442	0.000607	**0.008739*****
	(-6.284286)	**-26.42407**	**(15.23624)**	**(-15.53776)**	**(-1.781040)**	(-0.610528)	(1.137273)	**(9.744267)**
Variance Equation								
C	-4.478406	-3.770121	3.213564	-4.682761	-0.824474	-1.643582	-2.965814	-2.756257
	(-0.321773)	(-0.388172)	(0.027118)	(-0.583573)	(-0.002737)	(-0.022622)	(-0.191373)	(-0.732182)
ARCH	62.31569	5.416066	168.8871	6.051359	87.02810	10.27594	7.956732	3.217988
	(0.155560)	(0.267755)	(0.017538)	(0.354287)	(0.006704)	(0.029172)	(0.149630)	(0.393729)
Leverage	11.37521	0.407257	16.68910	-1.606020	-9.230848	2.833425	-0.074996	1.103296
	(0.154333)	(0.249835)	(0.017545)	(-0.350091)	(-0.006703)	(0.029179)	(-0.070733)	(0.387391)
GARCH	-0.080243	**-0.305464*****	-0.039642	**-0.427585*****	-0.009543	-0.059911	-0.159400	0.242084
	-1.167349	**(-2.940554)**	(-0.515590)	**(-4.463736)**	(-0.163045)	(-0.459974)	(-1.456054)	(2.3601171)
DVIX(-1)	**0.102685*****	0.052047	**0.086818****	-0.049185	0.052444	0.006995	0.075655	-0.034166
	(2.705928)	(1.357263)	**(2.093145)**	(-1.341107)	(1.193445)	(0.159605)	(1.489734)	(-0.574976)
ECBMPSI	**0.039556*****	0.004709	**0.020304***	0.012512	**0.026978****	0.019507	**0.026252****	**0.027810****
	(3.381643)	(0.415938)	**(1.827304)**	(1.167974)	**(1.978716)**	(1.620891)	**(2.355384)**	**(2.499708)**
FEDMPSI(-1)	**0.028576****	**0.030693****	**0.055420*****	**0.024365****	**-0.040630*****	0.009078	-0.006021	-0.008715
	(2.239208)	**(2.547974)**	**(4.530519)**	**(2.065635)**	**(-2.962897)**	(0.742122)	(-0.466014)	(-0.773531)
T-DIST. DOF	2.000049	2.004872	2.000008	2.004256	2.000024	2.001145	2.001964	2.012588

Significant coefficients (< 10% level) are given in bold-faced letters; significance levels: * < 10%,** < 5%,*** < 1%; z-values in parantheses; mean equations are specified based on the Schwarz criterion (see section 5.1); Estimation of all models as ML with EGARCH(1,1,1) specification assuming t-distributed errors and optimisation using the Eviews legacy algorithm with Marquard steps in all models.BIC gives the Schwarz-Bayes Information Criterion. ECBMPSI was lagged once in model (5) to avoid endogeneity problems.

Table 10: EGARCH-in-Mean Models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	DUS_OIS	$DUS10Y$	DUS_CORP	DUS_CORP_HY	$DXOIS$	$DXBUND$	$DXCORP\_Y$	$DXCORP\_HY$
Mean Equation								
GARCH	0.000120	-6.65E-06	0.000307	0.005895	-0.000219	-0.000908	-0.000620	**0.234844*****
	(0.827619)	(-0.003007)	(0.151924)	(1.470042)	(-0.710579)	(-0.411573)	(-0.374148)	**(2.671077)**
C	0.000421	-0.000837	-0.000844	0.042873	-0.000706	0.001702	-0.002116	-0.304170
	(0.7028)	(-0.16643)	(-0.013633)	(1.441888)	(-0.080515)	(0.001478)	(-0.062982)	(-0.026158)
DVIX	**-0.000355*****	**-0.015963*****	**0.012054*****	**-0.006598*****	**-0.000159***	**-0.005036*****	**-0.001638*****	**-0.026158*****
	(-6.455817)	**-25.97639**	**(14.78074)**	**(-10.57359)**	**(-1.722502)**	**(-8.062438)**	**(-3.648303)**	**(-3.325918)**
Variance Equation								
C	-4.523132	-3.663851	-0.850531	**-7.434103*****	-3.431676	2.470229	-2.135370	0.923531
	(-0.470277)	(-0.388494)	(-0.004143)	**(-5.076441)**	(-0.081480)	(0.002032)	(-0.037228)	(0.414007)
ARCH	58.40339	5.344029	23.47386	**0.309985*****	35.91690	95.65461	11.38814	0.464204
	(0.235978)	(0.277239)	(0.009924)	**(4.081082)**	(0.050201)	(0.001576)	(0.036888)	(0.643240)
Leverage	10.39249	0.403143	3.098492	0.008873	-3.280258	29.52816	0.097681	0.880016
	(0.233214)	(0.257592)	(0.009924)	(0.166719)	(-0.050191)	(0.001576)	(0.032783)	(0.659386)
GARCH	**-0.128392***	**-0.311668*****	-0.018871	0.033566	-0.056461	0.041789	-0.057995	**0.279813*****
	(-1.806820)	**(-3.039642)**	-0.259909	(0.173867)	(-1.030337)	(0.342023)	(-0.571428)	**(4.631262)**
DVIX	**0.106049*****	0.052038	**0.082411****	-0.008071	0.025341	**0.096129****	-0.002742	**0.142818*****
	(2.931549)	(1.359048)	**(1.979101)**	(-0.272490)	(0.567593)	**(2.238030)**	(-0.069165)	**(3.128005)**
ECBMPSI	**0.046357*****	-0.00663	**0.030812****	0.002829	-0.001585	**0.024377***	**0.030208*****	-0.001171
	(3.376351)	(-0.465319)	**(2.200826)**	(0.299583)	(-0.158226)	**(1.767270)**	**(2.694652)**	(-1.355664)
FEDMPSI	0.014643	**0.036765****	**0.042086*****	0.000979	**0.046988*****	0.008736	-0.012506	0.001420
	1.021342	**(2.425968)**	**(2.710903)**	(0.101584)	**(4.424726)**	(0.617517)	(-0.997050)	(1.478612)
T-DIST. DOF	2.000051	2.004988	2.000343	4.984492	2.000122	2.000014	2.001056	2.000288
BIC	-8.775250	-3.995762	-3.486722	-4.470004	-7.405392	-3.989583	-4.605459	-3.498024

Significant coefficients (< 10% level) are given in bold-faced letters; significance levels: * < 10%,** < 5%,*** < 1%; z-values in parantheses; mean equations are specified based on the Schwarz criterion (see section 5.1); Estimation of all models as ML with EGARCH(1,1,1) specification assuming t-distributed errors and optimisation using the Eviews legacy algorithm with Marquard steps in all models. BIC gives the Schwarz-Bayes Information Criterion. ECBMPSI was lagged once in model (5) and FEDMPSI lagged once in model (7) to avoid endogeneity problems.

Table 11: Residual Correlation Using Var in Levels and Differences

VAR in Differences

	DUS10Y	DUS_CORP	DUS_CORP_HY	DUS_OIS	DUSFF1M	DVIX	DXBUND	DXCORP_Y	DXCORP_HY	DXEONIA	DXOIS	DECBMPSI	DFEDMPSI
DUS10Y	1.000000												
DUS_CORP	−0.232478	1.000000											
DUS_CORP_HY	0.886253	−0.054648	1.000000										
DUS_OIS	0.281811	−0.128790	0.323901	1.000000									
DUSFF1M	0.049903	−0.033797	0.062790	0.103343	1.000000								
DVIX	−0.365259	0.472402	−0.250892	−0.171167	−0.003060	1.000000							
DXBUND	0.600881	−0.169905	0.561055	0.157824	−0.007553	−0.172810	1.000000						
DXCORP_Y	0.387913	0.033009	0.409418	0.045596	−0.004035	−0.035781	0.744097	1.000000					
DXCORP_HY	−0.156602	0.486512	−0.037626	−0.107220	0.005745	0.292500	−0.064417	0.207665	1.000000				
DXEONIA	−0.006196	−0.023278	−0.036791	0.046866	−0.021744	0.015948	−0.013243	0.005066	0.014710	1.000000			
DXOIS	0.097789	−0.040051	0.092341	0.067059	−0.079669	−0.040488	0.189747	0.208013	−0.042474	0.101069	1.000000		
DECBMPSI	0.043056	0.014718	0.026756	0.012488	0.042375	0.038764	0.053454	0.056064	0.019245	−0.025664	−0.077922	1.000000	
DFEDMPSI	0.002753	0.026137	−0.003602	0.010886	0.028832	0.002272	0.017999	0.071593	0.084173	0.019326	−0.032082	0.606408	1.000000

Notes: Results are estimated based on an unrestricted VAR in first differences including one lag, selected based on Schwarz and Hannan-Quinn LM-lag length criteria. Estimating a VAR with all variables in first differences is following the results of the ADF test, where depending on the assumptions on deterministic terms, we cannot reject unit roots on a 5% level for any of the variables. "X" indicates dollarised variables, i.e. variables variables multiplied by the USD/EUR exchange rate. "US" indicates american indices and VIX is the CBOE VIX volatility index.

VAR in Levels

	US10Y	US_CORP	US_CORP_HY	US_OIS	USFF1M	VIX	XBUND	XCORP_Y	XCORP_HY	XEONIA	XOIS	ECBMPSI	FEDMPSI
US10Y	1.000000												
US_CORP	−0.200647	1.000000											
US_CORP_HY	0.885822	−0.022961	1.000000										
US_OIS	0.287327	−0.139349	0.322199	1.000000									
USFF1M	0.063364	−0.057283	0.064930	0.080555	1.000000								
VIX	−0.357156	0.461250	−0.235641	−0.173438	−0.001904	1.000000							
XBUND	0.585517	−0.147100	0.558193	0.173238	0.024410	−0.161052	1.000000						
XCORP_Y	0.388363	0.049781	0.416621	0.052315	−0.003437	−0.026480	0.751066	1.000000					
XCORP_HY	−0.156304	0.516550	−0.055120	−0.206407	−0.012941	0.348234	0.016248	0.315695	1.000000				
XEONIA	0.003673	−0.023355	−0.026714	0.046255	−0.020108	0.006463	0.009991	0.030619	0.012226	1.000000			
XOIS	0.103285	−0.047595	0.101966	0.076745	−0.044042	−0.028859	0.217593	0.224228	−0.027293	0.106082	1.000000		
ECBMPSI	0.061014	−0.041082	0.019017	0.037513	0.030313	0.001654	0.022449	0.011043	−0.043013	$-4.25E-05$	−0.074524	1.000000	
FEDMPSI	0.013865	−0.009285	0.004131	0.026597	0.023886	−0.010217	0.018102	0.056480	0.065940	0.039998	−0.046479	0.609028	1.000000

Notes: Results are based on estimated an unrestricted VAR in levels including one lag, selected based on Schwarz and Hannan-Quinn LM-lag length criteria. "X" indicates dollarised variables, i.e. variables variables multiplied by the USD/EUR exchange rate. "US" indicates american indices and VIX is the CBOE VIX volatility index.

D Technical Appendix

D.1 Portfolio Optimization

Assume an economy with two types of agents – arbitrageurs and investors. Arbitrage arises as holding return $R^P_{(t,t+1)}$ of a security between two respective periods. Eq. (6) describes arbitrageurs' preferences based on a mean-variance objective function:

$$E_t R^P_{(t,t+1)} - \frac{1}{2}\sigma Var_t R^P_{(t,t+1)} \tag{6}$$

$$R^P_{(t,t+1)} = \sum_{i=1}^{N} \omega^i_t R^i_{(t,t+1)} = \sum_{i=1}^{N} \omega^i_t [exp(\overline{p}^i_{t+1} - \overline{p}^i_t) - 1]$$

where ω^i_t represents the share arbitrageurs' holdings of bonds in habitat i relative to their net wealth W_t, and $\overline{p}^i_t$ is the price of a bond in habitat i at time t. These bonds are subject to credit risk, measured as risk intensity parameter ψ_t, such that

$$\overline{P}^{(0)}_{t+1} = \begin{cases} 1, & \text{with probability } exp(-\psi_{t+1}). \\ 0, & \text{with probability } 1 - exp(-\psi_{t+1}) \end{cases},$$

which is affine in a set of macroeconomic factors

$$\psi_{t+1} = \gamma' X_{t+1} \tag{7}$$

which follow the VAR process

$$X_t = \mu + \Phi X_{t-1} + \varepsilon_t \qquad \varepsilon_t \sim N(0, \Sigma\Sigma') \tag{8}$$

with log-bond prices of a pure-discount habitat i, default-risk-less bond given as

$$\overline{p}^i_t = -\overline{a}_i - \overline{b}'_i X_t, \tag{9}$$

its corresponding risk-free one-period rate as

$$y^i_t = a_i + b'_i X_t,$$

and the continuously compounded yield y^i_t on a n-period bond in habitat i as $-p^i_t/n$.

Arbitrageurs' portfolio holding return can be expressed as

$$\begin{aligned} R^P_{(t,t+1)} &= \sum_{i=1}^{N} \omega^i_t [exp(-\overline{a}_i - \overline{b}'_i X_{t+1} + \overline{a}_i + \overline{b}'_i X_t) - 1] \\ &= \sum_{i=1}^{N} \omega^i_t [exp(\overline{b}'_i (X_t - X_{t+1})) - 1], \end{aligned} \tag{10}$$

where an arbitrageur chooses ω_t^i such that[13]

$$\begin{aligned} &\max \;\; E_t[R^P_{(t,t+1)}] - \frac{1}{2}\sigma Var_t[R^P_{(t,t+1)}] \\ &s.t. \;\; : \;\; \sum_{i=1}^{N} \omega_t^i = 1 \end{aligned} \tag{11}$$

where for small time increments we can approximate the conditional variance, $Var_t[R^P_{(t,t+1)}]$, and the conditional expected mean return, $E_t[R^P_{(t,t+1)}]$, such that[14]

$$\begin{aligned} E_t[R^P_{(t,t+1)}] &\approx \sum_{i=1}^{N} \omega_t^{(i)}[(-(\overline{b}_i' + \gamma')(\mu + \Phi X_t) \\ &\quad + \frac{1}{2}(\overline{b}_i' + \gamma)\Sigma\Sigma'(\overline{b}_i' + \gamma) + \overline{b}_i' X_t]) \\ Var_t[R^P_{(t,t+1)}] &\approx d_t'\Sigma\Sigma' d_t, \end{aligned} \tag{12}$$

where

$$d = \sum_{i=1}^{N}(\omega_t^i(\overline{b}_i + \gamma))$$

represents a factor of exposure to macroeconomic risk.

[13]The mean-variance objective function in (14) can be seen as no-arbitrage condition, where any positive difference, must be the result of an arbitrage opportunity, realised through the choice of ω_t^i.

[14]Hamilton and Wu (2012) Hamilton and Wu (2012) show that for $q_{n,t+1} \equiv \frac{P_{(i,t+1)} - P_{it}}{P_{it}} = \exp\left(\mu_i h + \sqrt{h}\epsilon_{i,t+1}\right) - 1$, $(\epsilon_{1,t+1}, ..., \epsilon_{N,t+1})' \sim N(0, \Omega)$, the continuous time representation of a discrete time process,

$$\begin{aligned} E_t\left(\sum_{i=1}^{N} z_{it} R^P_{(t,t+1)}\right) &= \sum_{i=1}^{N} z_{it}[\mu_i h + \Omega_{ii} h/2 + o(h)] \\ Var_t\left(\sum_{i=1}^{N} z_{it}\right) &= z_t'\Omega z_t h + o(h), \end{aligned}$$

for $h = 1$ and $o(h) = 0$ leads to

$$\begin{aligned} \frac{P_{(i,t+1)}}{P_{it}} &= \exp[\overline{b}_i'(X_{t+1} - X_t)] \\ \mu_n &= \overline{b}_i'(c + \gamma X_t) - \overline{b}_i' X_t \\ \Omega_{ii} &= \overline{b}_i'\Sigma\Sigma'\overline{b}_i, \end{aligned}$$

which implies (12).

The FOCs of the Lagrangean, L_t, corresponding with (12) are

$$\begin{aligned}\frac{\partial L_t}{\partial \omega_t^i} &= -(\overline{b}_i' + \gamma')(\mu + \Phi X_t) + \frac{1}{2}(\overline{b}_i' + \gamma)\Sigma\Sigma'(\overline{b}_i' + \gamma) + \overline{b}_i' X_t) \\ &\quad -(\overline{b}_i' + \gamma')\Sigma\Sigma'\sigma\sum_{i=1}^{N}[\omega_t^i(\overline{b}_i + \gamma)] - \chi_t = 0,\end{aligned} \tag{13}$$

where χ_t is the Lagrange multiplier of the constraints.

Expressing the FOCs in terms of excess holding returns then yields

$$\begin{aligned}\text{where} \qquad R^i_{(t,t+1)} - \overline{r}_t &= \overline{b}_i'\Sigma\Sigma'\lambda_t \\ R^i_{(t,t+1)} &\equiv -\overline{b}_i'(\mu + \Phi X_t) + \frac{1}{2}(\overline{b}_i' + \gamma')\Sigma\Sigma'(\overline{b}_i + \gamma) \\ &\quad -\frac{1}{2}\gamma'\Sigma\Sigma'\gamma + \overline{b}_i' X_t \\ \overline{r}_t &= \overline{a}_i + \overline{b}_i' X_t \\ \lambda_t &\equiv \sigma\sum_{i=1}^{N}(\omega_t^i(\overline{b}_i + \gamma))\end{aligned} \tag{14}$$

Investors follow their preferred-habitat motifs over specific maturities in their demand as

$$\xi_t^i = \varphi(\overline{y}_t^i - \beta^i) \tag{15}$$

where ξ_t^i is the demand relative to the arbitrageurs' net wealth W_t, and β^i its intercept. In equilibrium the combined demand from arbitrageurs and investors then needs to equal the supply of bonds S_t^i

$$\omega_t^i + \xi_t^i = S_t^i \tag{16}$$

which combined with (14) gives the market price of risk as

$$\lambda_t = \sigma\sum_{i=1}^{N}(S_t^i - \xi_t^i)(\overline{b}_i + \gamma) \tag{17}$$

Using 15 in 17 and rearranging the FOCs in terms of bond yields, $\overline{y}_t^i$, gives

$$\begin{aligned}&\overline{y}_t^i = \frac{1}{2}E_t(r_t + r_{t-1} + \ldots) + \frac{1}{n}E_t(\gamma'(\mu + \Phi X_t) + \gamma'(\mu + \Phi X_{t+1}) + \ldots) \\ &\frac{1}{n}E_t((\overline{b}_i' + \gamma')\Sigma\Sigma'\lambda_t + (\overline{b}_i' + \gamma')\Sigma\Sigma'\lambda_{t+1} + \ldots) - \frac{1}{2}(\overline{b}_i' + \gamma')\Sigma\Sigma'(\overline{b}_i + \gamma)\end{aligned} \tag{18}$$